REPORT DOCUMENTATION PAGE

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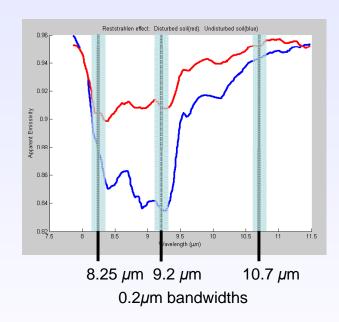


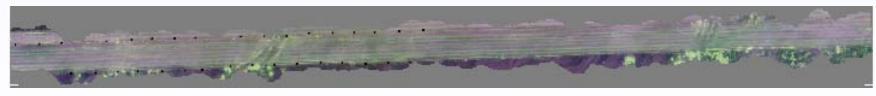
Buried Target Detection using a 3-band LWIR Airborne Sensor

Signal Innovations Group, Inc.

Three-Band Data from SCISSOR (Shadow-Class Infrared Spectral SensOR)

- •Three bands chosen within and just outside the Restrahlen band.
- •SCISSOR data collected using a helicopter flyover.
- •Buried targets marked by fiducials including pressure plates, 155 rounds, and empty holes.



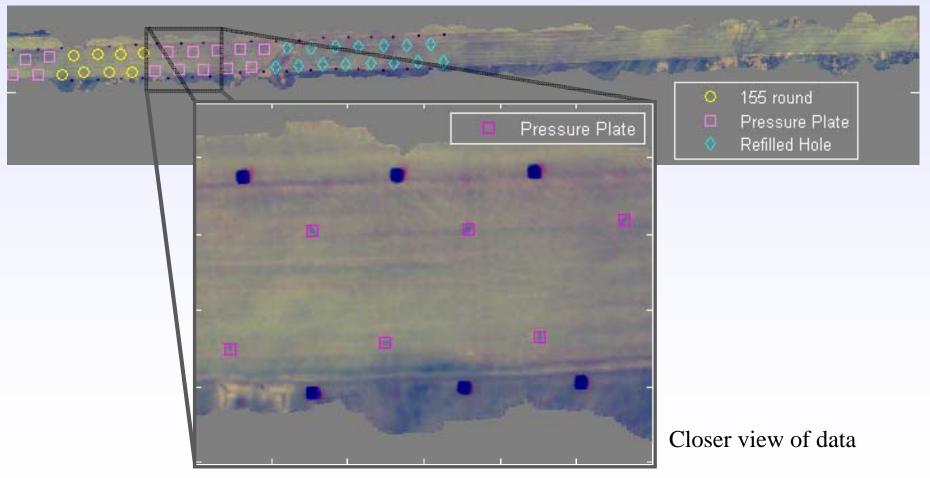


Flight path



Area of study

Set of fiducial marked targets, including 14 pressure plates

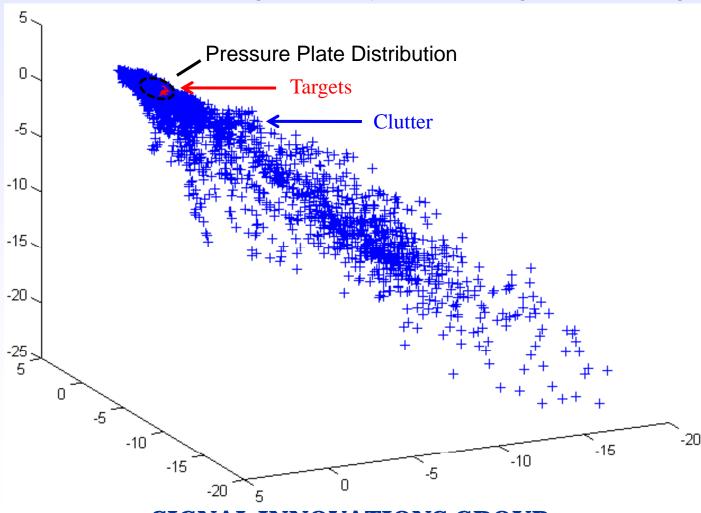


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Scatter Plot of Whitened Radiance Data

Spectral features are not enough to clearly separate targets from background



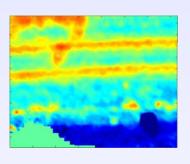


Objectives

- Maximize detection of buried targets while minimizing false alarms.
- Explore a variety of RX-family detectors that could be useful for buried target detection within varying background complexities.
- Provide an overall framework for buried target detection using a combination of anomaly detection followed by spectral and spatial feature classification.



Overall Approach



Features: Spectral and relative spatial information

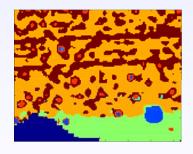
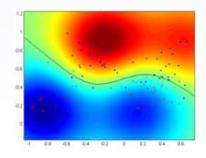


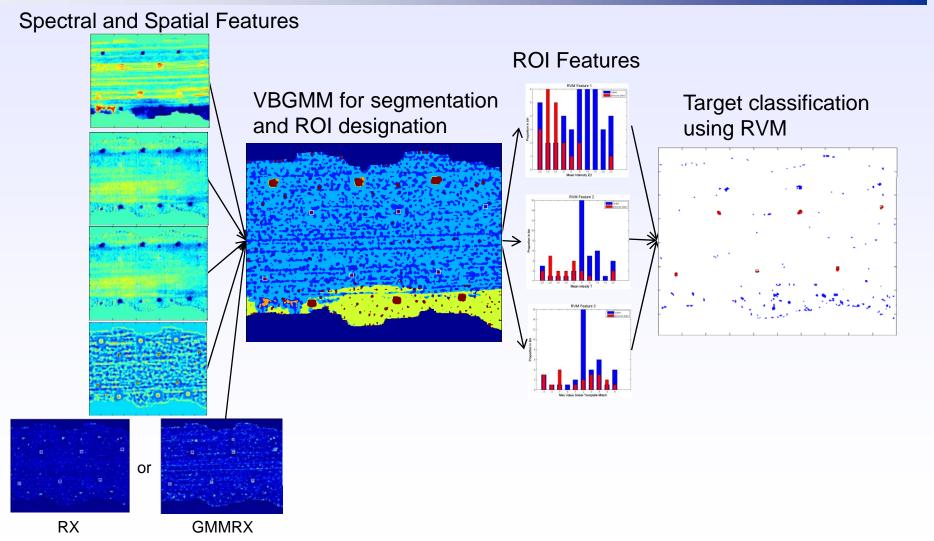
 Image segmentation to find regions of interest (ROIs) using a variational Bayesian Gaussian mixture model.



 Classification of each ROI as a target or clutter using a relevant vector machine (RVM).

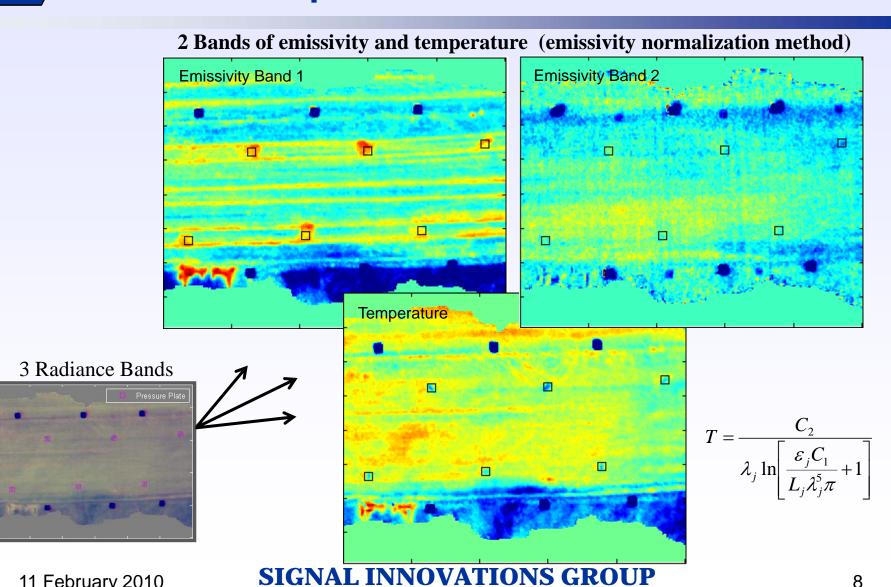


Overall Process





Spectral Features



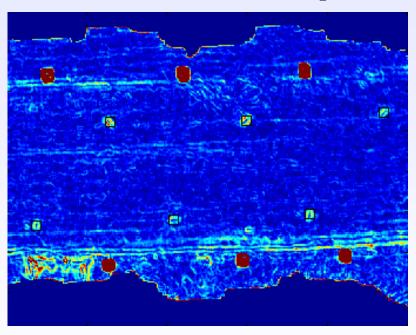
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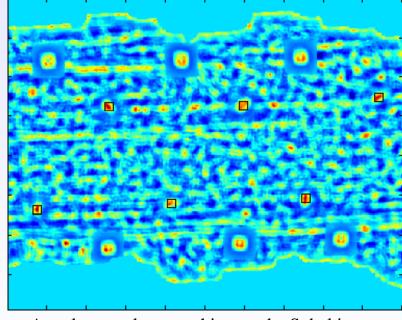


Spatial Features: Gradient (Sobel) and Size/Shape Templates

Sobel operator with template matching



Edge detection with Sobel operator



Annular template matching on the Sobel image

Step 1 Step 2

A Sobel operator is used on the spectral data to find edges within the image, revealing the buried targets as rings. An annular template, the size of the target rings, is applied to the Sobel image, providing a final image displaying where the centers of the rings are (likely target locations).

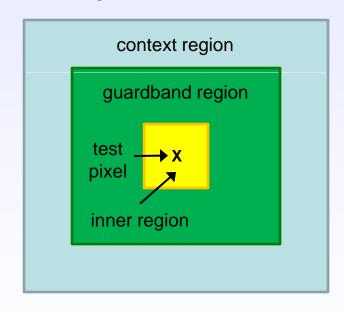


Spatial Anomaly Measure: RX family

 Standard RX anomaly detector assumes that points in context region are from a multivariate Gaussian density

$$RX = \left(\overline{X}_{inner} - \overline{X}_{context}\right)^{T} \Sigma_{context}^{-1} \left(\overline{X}_{inner} - \overline{X}_{context}\right)$$

- This assumption is violated when the local context region is abruptly changing or composed of multiple types of background signals
- NEW APPROACH: Model context region pixels with a Gaussian mixture model using local and global context



- Use a variational Bayesian Gaussian mixture model (GMMRX) to learn clusters globally for an entire image
- Use globally learned clusters to create local GMMs (local GMMRX) for each context region



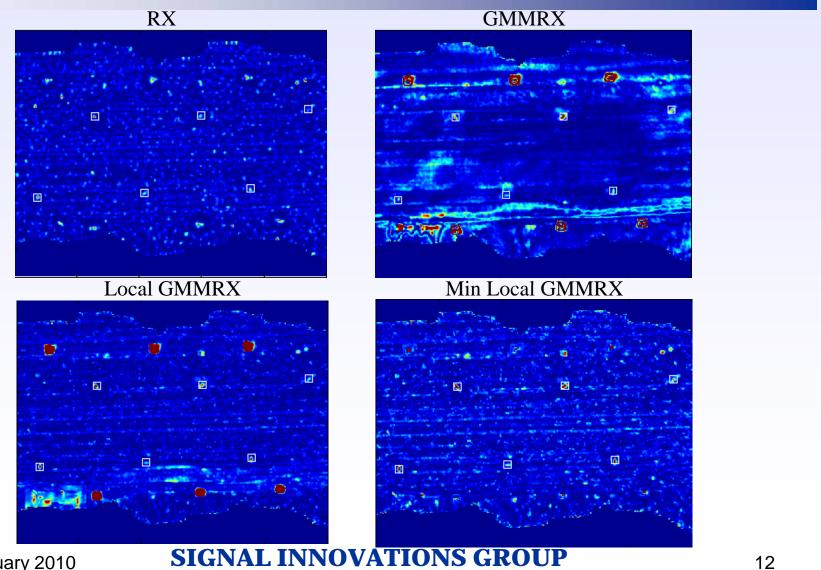
Comparison of approaches

	RX	GMMRX	Local GMMRX	Min Local GMMRX
Strengths	Detecting anomalies in relatively smooth, well-behaved regions	Detecting anomalies in relatively smooth, well-behaved regions (usually) Detecting anomalies in rapidly varying background	Detecting anomalies in smooth regions Detecting anomalies in rapidly varying background Detecting anomalies that differ from at least some local context clusters	Detecting anomalies in smooth regions Detecting anomalies that differ from <u>all</u> local context clusters
Weaknesses	Detecting anomalies in rapidly varying background	Detecting anomalies that do not differ substantially from globally-learned parameters (even if they are noticeably different from local context pixels)	May detect more unwanted anomalies since any anomaly that differs from at least some local context clusters will be detected	Detecting anomalies that differ from some local context clusters but not all (can cause a problem when trying to detect anomalies in rapidly varying background)

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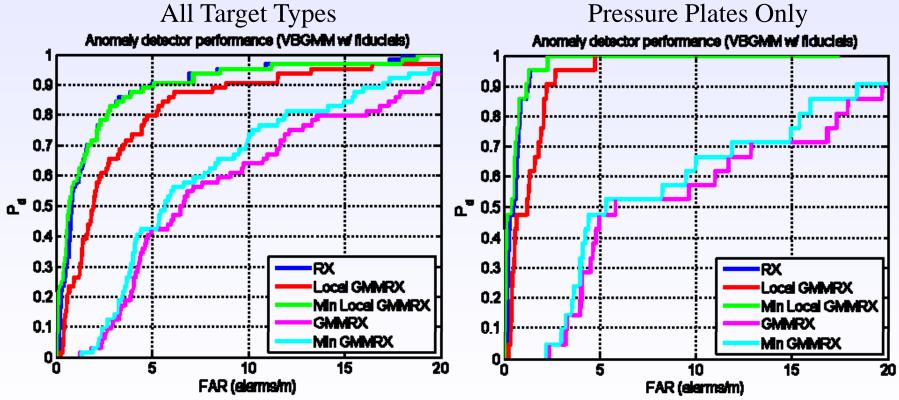
Spatial Features: RX family





RX Performance

RX detector only, not with the comprehensive detection process.

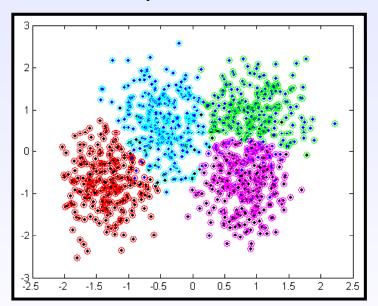


Since they perform the best, the standard RX and the Min GMMRX are both used as features in the overall target detection process described. Min GMMRX is referred to as GMMRX in the remainder of the slides for convenience.

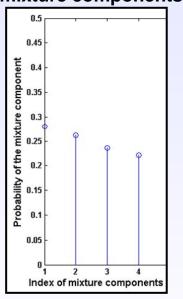


Unsupervised clustering using VBGMM

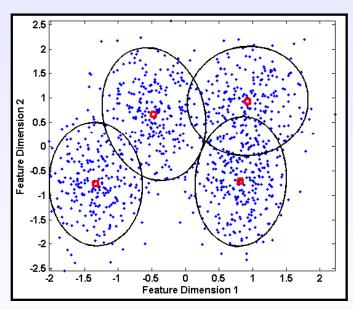
2D data sampled from 4 Gaussians



4 VBGMM non-zero mixture components



VBGMM clusters

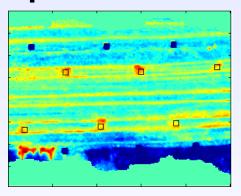


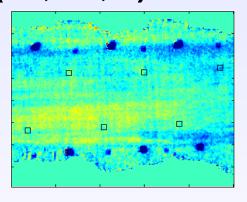
- The number of clusters is determined by the algorithm.
- Complex models are penalized, guiding the algorithm to choose the best fit using the least number of clusters.

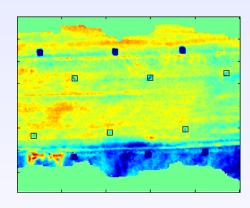
$$\mathbb{F}_{m}[q] = \int d\Theta q(\Theta) q(k) \log \frac{p(D, \Theta, k)}{q(\Theta)q(k)} = \langle \log \frac{p(D, k|\Theta)}{q(k)} \rangle_{k,\Theta} - KL[q(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p(\Theta)||p$$

Features used for VBGMM image segmentation

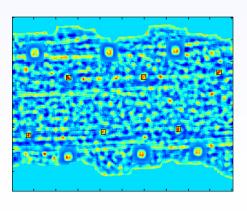
Spectral Features(E2, E3, T)

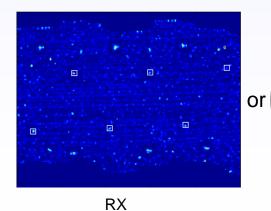






Spatial Features (Sobel with Template Matching, RX)





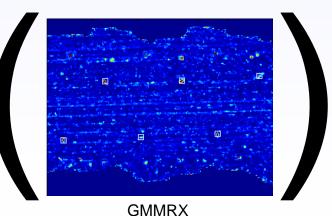
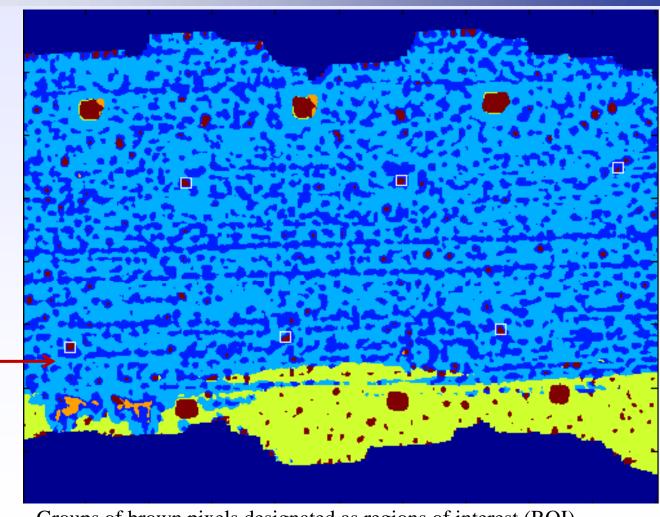




Image segmentation using VBGMM



Groups of brown pixels designated as regions of interest (ROI).

Regions of

Interest

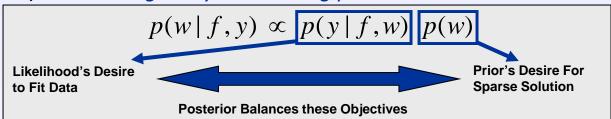


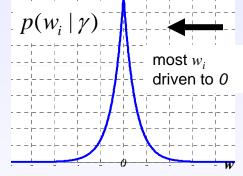
Relevance Vector Machine

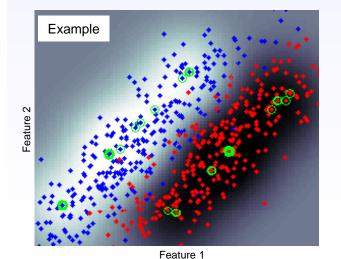
• RVM functional form is kernel-space hyperplane classifier: $f(\mathbf{x}) = \mathbf{w}^T \phi_n(\mathbf{x})$

Bayesian learning: prior on weights to induce sparse solution (i.e., most weights driven to

zero) - learn weights by maximizing posterior







- Example Automatic relevance determination (ARD)
 - Adopt hierarchical Bayes model zero-mean Gaussian prior with exponential hyper-prior on independent variances, t_i

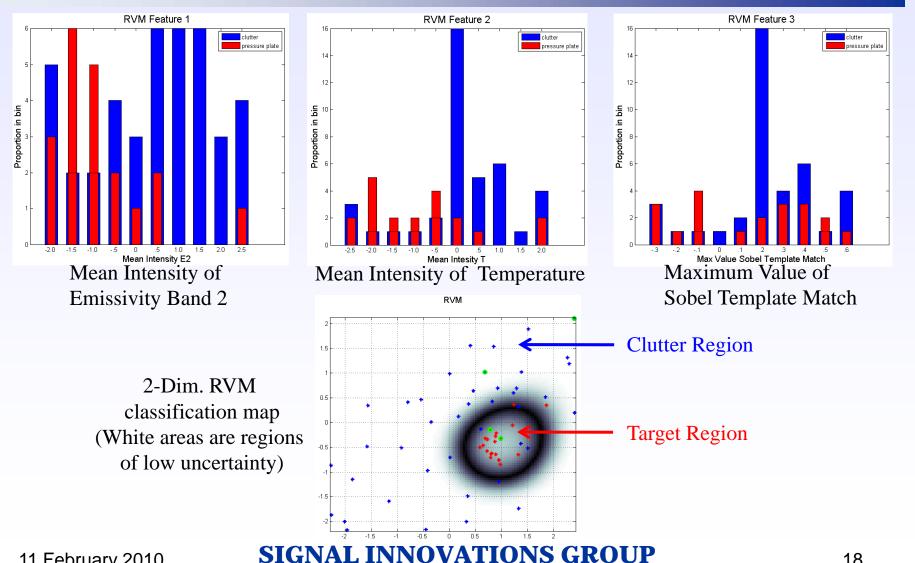
$$p(w_i | \tau_i) = N(w_i | 0, \tau_i)$$
 $p(\tau_i | \gamma) = (\gamma/2) \exp\{-\gamma \tau_i/2\}$

- Integration with respect to t_i recovers Laplacian form
 - Allows for expectation-maximization (EM) iterative optimization

$$p(w_i \mid \gamma) = \int_{0}^{\infty} p(w_i \mid \tau_i) p(\tau_i \mid \gamma) d\tau_i = (\gamma/2) \exp\{-\sqrt{\gamma} |w_i|\}$$

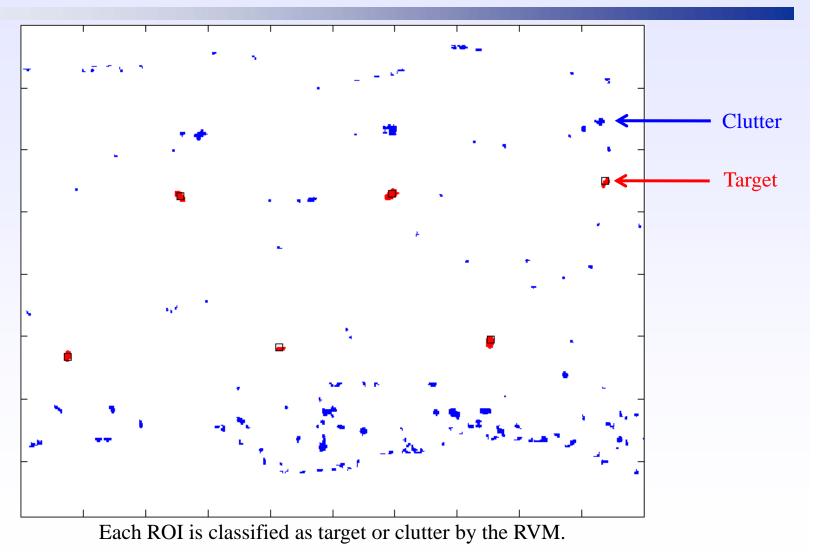


ROI Features used with RVM



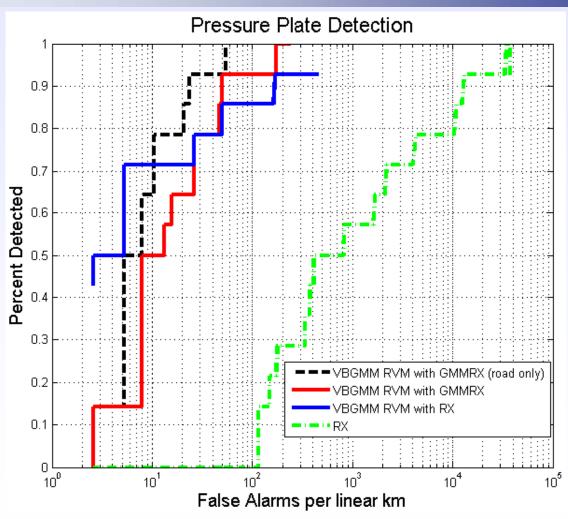


ROI classification using RVM





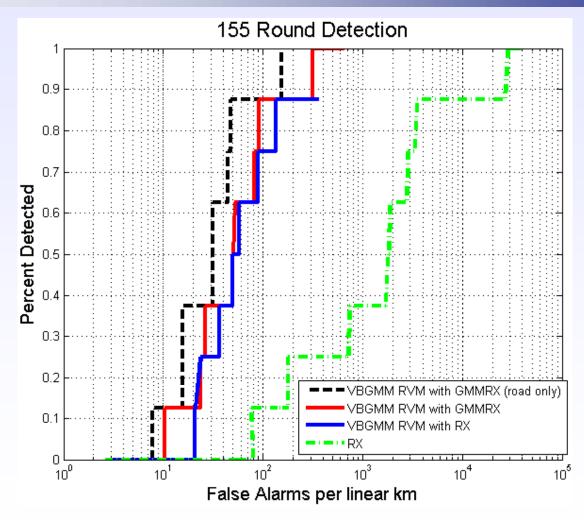
Results on pressure plate detection



 $Image: scan_1500_20_off_cm_EW_run1_090723_063623_rad_mfilt_median_3band_12600-14700_TRIGEO_rotreg_merge_geomerge.xv$



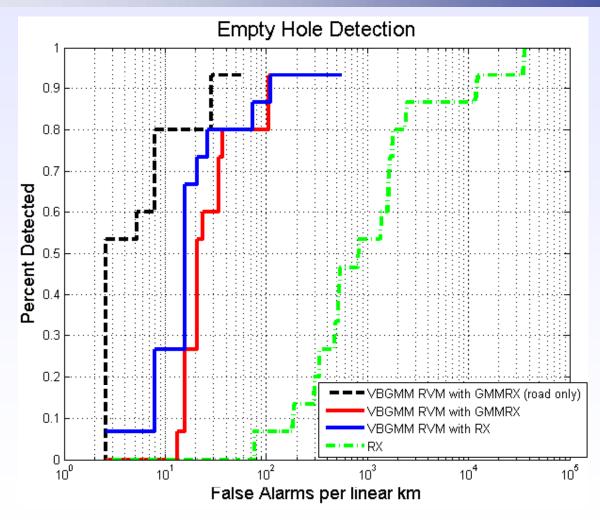
Results on 155 round detection



 $Image: scan_1500_20_off_cm_EW_run1_090723_063623_rad_mfilt_median_3band_12600-14700_TRIGEO_rotreg_merge_geomerge.xv$



Results empty hole detection



 $Image: scan_1500_20_off_cm_EW_run1_090723_063623_rad_mfilt_median_3band_12600-14700_TRIGEO_rotreg_merge_geomerge.xv$



Results on pressure plate, 155 round, and empty hole detection

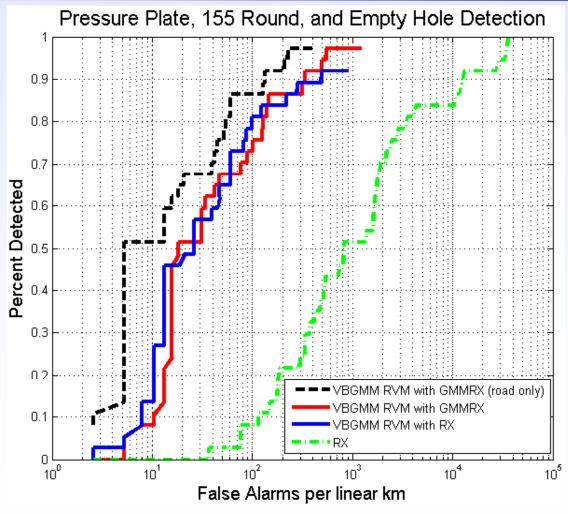


Image: scan_1500_20_off_cm_EW_run1_090723_063623_rad_mfilt_median_3band_12600-14700_TRIGEO_rotreg_merge_geomerge.xv



Summary

- The comprehensive approach, using both spectral and spatial features, VBGMM for image segmentation to find ROIs, and RVM to classify ROIs that are targets works far better than the windowed RX detector alone in detecting buried targets.
- Pressure plates are the target best detected, and the 155 rounds are the most difficult to detect.
- GMMRX as a feature used in the comprehensive approach performs best at higher probability of detection levels, particularly when restricting the search zone only to the road.
- In a setting where targets are placed within a more heterogeneous background (i.e., off road or side of road), the RX feature would likely miss many more targets than GMMRX, providing a clear advantage in using GMMRX.



Follow On Work

- Improve target detection by representing spatial pixel blocks of spectral data as a mixture of base distributions, and performing unsupervised clustering using the Dirichlet process.
- Develop a fully Bayesian approach to emissivity and temperature extraction from multiband radiance data.
- Consider a noise model in buried target detection within a fully Bayesian setting.